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Jurnal Pensil Pendidikan Teknik Sipil

Journal homepage: http://journal.unj.ac.id/unj/index.php/jpensil/index

COST AND TIME EFFICIENCY ANALYSIS OF ROAD CONDITION SURVEYS: MANUAL VS SEMI-AUTOMATED METHODS

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P-ISSN: 2301-8437
E-ISSN: 2623-1085

ARTICLE HISTORY
Accepted:
17 July 2025
Revision:
24 September 2025
Published:
30 September 2025

ARTICLE DOI:
10.21009/jpensil.v14i3.58676

Abstract

Roads are a fundamental component of transportation that plays a critical role in national economic growth. Maintaining road conditions is essential to ensure optimal traffic serviceability. However, in developing countries like Indonesia, these surveys are predominantly conducted manually. This conventional approach is time-consuming, costly, and requires a substantial amount of human resources. The swift progression of machine learning (ML) within Artificial Intelligence (AI) presents an opportunity to be utilized as a data processing tool for road condition surveys, leading to greater time and cost efficiency. This study analyzes the cost and time required for two survey methods: manual and semi-automated, employing machine learning. Based on the analysis conducted on 164 km of urban roads in Bandung City, the semi-automated ML method achieved a cost efficiency of 72.23%, with its total cost being only 27.77% of the manual method. Furthermore, the time efficiency reached 96.34%, meaning the survey was completed in just 3.66% of the time required by the manual approach. These results indicate that the application of machine learning for semi-automated road condition surveys is substantially more efficient in terms of both time and cost compared to traditional manual surveys.

Keywords: Time Efficiency, Cost Efficiency, Road Condition Survey, Manual Survey Method, Semi-automated Survey Method, Machine Learning

Introduction

Roads represent a fundamental transportation infrastructure, serving as the backbone for the mobility of people and goods, and a primary driver of a nation's economic growth (Nawir et al., 2023; Pantuso et al., 2019; Utama et al., 2023). To ensure that this infrastructure functions optimally and safely, the condition of the road pavement must be consistently maintained (Kamenchukov et al., 2018; Liu, 2014; Rhoma Putra et al., 2022). Effective road maintenance programs are highly dependent on accurate and up-to-date data on road conditions (Pasiak et al., 2020; Susantio, 2015), which is acquired through periodic surveys (Aflaki & Hajikarimi, 2011). Reliable pavement condition data allows for the identification of maintenance needs, prioritization of repairs, and allocation of resources, ensuring that interventions are both timely and cost-effective (Radopoulou & Brilakis, 2016). Data-driven approaches help address maintenance backlogs and optimize investments, especially in developing countries where budgets are limited (Al-Mansour & Al-Qaili, 2022; Pantuso et al., 2019).

Conventionally, particularly in developing countries like Indonesia, road condition surveys predominantly rely on manual methods (Espinet et al., 2017; Fukai et al., 2021; Utami et al., 2023). This process involves teams of surveyors conducting direct on-site visual inspections to identify and document various types of pavement distress (Bianchini et al., 2010; Pikal et al., 2024; Qureshi et al., 2022; Wan et al., 2022; Widjajanto et al., 2017). Despite its long-standing application, this method has significant limitations. Its primary drawbacks are that it is labor-intensive, time-consuming, and incurs high operational costs (Afrizal, 2020; H. Dong et al., 2022; Radopoulou & Brilakis, 2016; Ragnoli et al., 2018; Shtayat et al., 2020). Another obstacle occurred when it was used for road condition surveys, especially large-scale ones conducted by government agencies. Furthermore, manual methods are susceptible to the subjectivity of individual assessors, which can compromise the consistency and accuracy of the data collected (Bogus et al., 2010; Shirvaikar et al., 2023; Tasmin et al., 2022).

In line with recent technological advancements, Artificial Intelligence (AI) and its subfield, machine learning (ML), have begun to revolutionize numerous sectors, including transportation engineering (Alam, 2022; Fauzi et al., 2024; Rahmawati et al., 2025; Zöller & Huber, 2021). The capacity of machine learning to recognize patterns within vast datasets offers immense potential for automating tasks that traditionally require human analysis (Selvi et al., 2022). Within the context of infrastructure maintenance, this technology has already been applied for traffic management, safety analysis, and asset condition monitoring (Ruseruka et al., 2023; Srikanth et al., 2024).

Previous studies have indicated that road condition surveys require more effective and efficient methods in terms of time, cost, and human resources. Recent developments in survey methods explored in prior research include the use of GPS to detect damage locations (Al-Mansour & Al-Qaili, 2022; D. Dong & Li, 2021; Yastawan et al., 2021), unmanned aerial vehicles (UAVs) to capture aerial imagery of road surface defects (Lebaku et al., 2024; Utami et al., 2023), and machine learning techniques for automated damage detection (Volkov et al., 2024). The application of machine learning has given rise to semi-automated methods for conducting road condition surveys (Chhabra & Singh, 2021; Luo et al., 2022). Integration of these advanced technologies minimizes the need for subjective and time-consuming human interventions, thereby enhancing the repeatability and cost-effectiveness of the asset inventory process (Hecht et al., 2025; Ho, 2020; Kargah-Ostadi et al., 2020).

In addition to manual or conventional methods, data collection and road damage identification can also be carried out semi-automatically and automatically (Marga, 2021). In this semi-automated approach, visual data, such as high-resolution video or images, are captured from a moving vehicle (Ruseruka et al., 2023; Ukhwah et al., 2019). This data is subsequently processed by a machine learning model called YOLOv8n that has been trained to automatically detect and classify road distress. Compared to other models, YOLO is open source and excels in terms of accuracy, processing speed, and resistance to noise and interference, making it ideal for real-time detection (Bilous et al., 2024; Jiang, 2024). This approach promises a survey process that is faster, more objective, and potentially more cost-effective (Denaro & Lim, 2025; D. Dong & Li, 2021; Llopis-Castelló et al., 2024), especially for large-scale use (Alqaydi et al., 2024).

Considering the inherent limitations of manual methods and the significant potential offered by semi-automated approaches, a quantitative evaluation of these two methodologies is imperative. The urgent need to achieve greater cost and time efficiency in the maintenance of public infrastructure provides the core rationale for this research (Kargah-Ostadi et al., 2020). Therefore, this study quantitatively analyzes and compares the cost and time efficiency of the conventional manual survey method against a semi-automated method based on machine learning. A case study will be conducted on urban road sections in Bandung City to determine the magnitude of efficiency that can be achieved through the adoption of modern technology for road condition surveys.

Research Methods

This study utilized both manual and semi-automated methods to survey a 1 km segment of a primary road, Jalan Terusan Jakarta (Terusan Jakarta Street). The data obtained from this survey were subsequently used as a basis for the cost and time analysis for surveying 164 km of urban roads in Bandung. The research methodology is shown in Figure 1.

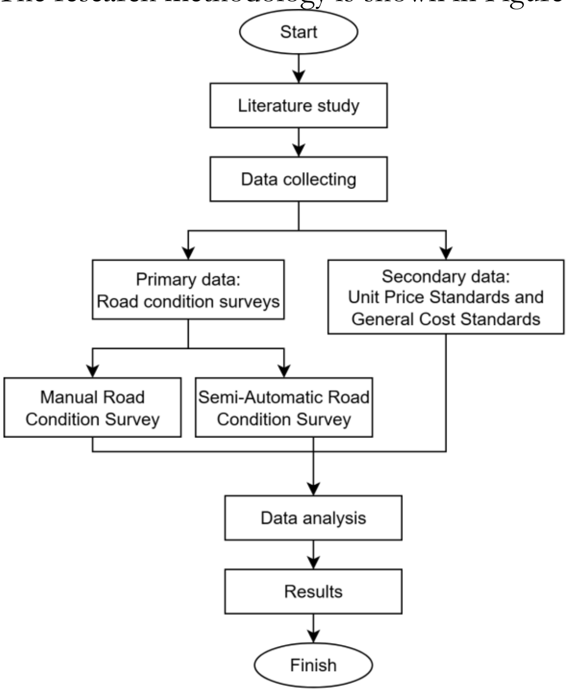

Figure 1. Research Methodology Flowchart

The data collection process in this study was systematically conducted to gather all necessary information. This stage was divided into the collection of two main types of data: primary and secondary data. Primary data was acquired directly from the field through comprehensive road condition surveys. To ensure a thorough assessment, two distinct methods were employed for this survey: a Manual Road Condition Survey and a Semi-Automatic Road Condition Survey. This dual-method approach allowed for both detailed on-site inspection and efficient data gathering over larger areas. Concurrently, secondary data was collected to support the analysis of the primary data. This included official Unit Price Standards and General Cost Standards. These standards provided the necessary financial and costing benchmarks required for the subsequent data analysis phase of the research.

Both manual and semi-automated methods assess road conditions based on the Surface Distress Index (SDI) methodology (Satheesan et al., 2024). The SDI method is a visual assessment of road conditions through road condition surveys (Pratomo et al., 2023; Prayudyanto et al., 2024; Yastawan et al., 2021). The manual survey method is conducted via direct on-site inspection, where a surveyor traverses the road and records the findings on a survey form (Bogus et al., 2010) as shown in Figure 2. Identification based on manual or traditional methods includes visual observation of damage, measuring the dimensions of damage, and conducting field documentation (Mustakim, 2023). Only then is an assessment of the damage reviewed, and the results of the observations recorded on a form before being reported (Sembiring et al., 2022). The data is subsequently processed to calculate the SDI value, which determines the road's condition.

Figure 2. Manual Road Condition Survey

The semi-automated method, in contrast, employs the YOLOv8n model to detect pavement distress, specifically potholes and cracks (Tsai et al., 2017). The survey for this method involves collecting a dataset of road condition videos, which are captured using a smartphone or a camera mounted on a moving vehicle (Arya et al., 2021, 2024; Maeda et al., 2018; Zhang et al., 2024). This approach ensures the model trains on data with high ecological validity, directly reflecting real-world conditions, as illustrated in Figure 3.

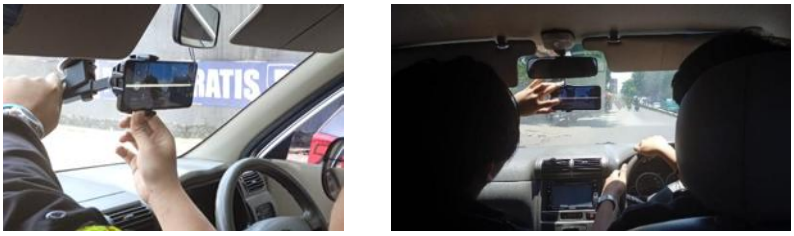

Figure 3. Semi-Automated Road Condition Survey

The video dataset is then processed through a high performance fine-tuned YOLOv8n model which is validated by a mean Average Precision (mAP50) of 0.960, which has been trained to identify potholes and cracks. The resulting detection information is subsequently used to compute the SDI value. The process will be faster than the manual method because the data acquisition is just collecting video of the road condition. The pavement distress type that is detected with machine learning is currently limited to pothole and crack, excluding rutting distress.

The consistency of the two methods differs fundamentally. Manual surveys are inherently vulnerable to inconsistencies such as low inter-rater reliability, subjective defect classification, and surveyor fatigue (labour-intensive)(Coenen & Golroo, 2017). In stark contrast, the semi-automated data collection and YOLOv8-based method is deterministic and objective, guaranteeing repeatable results from the same input data. This core reliability establishes the automated approach as a more robust and standardized tool.

In this study, the primary variables for comparison are cost and time. The data for these resources were gathered through primary surveys and from secondary sources. Efficiency is measured by comparing the output produced to the input used (cost of output) (Lona et al., 2023). Efficiency is quantified by the savings in cost and time achieved by the semi-automated method relative to the manual survey (Berlian P. et al., 2016; Irfan, 2019).

$$Saving\ efficency = \frac{Saving\ resources}{Manual\ survey\ resources} \times 10$$

To classify the level of cost and time efficiency, an efficiency ratio is computed by comparing the resources (cost or time) utilized in the semi-automated survey to those of the manual survey. This ratio is subsequently used to determine whether the resulting resource savings fall into the categories of highly efficient, efficient, moderately efficient, inefficient, or not efficient. The efficiency ratio is formulated as follows (Lona et al., 2023).

$$Efficiency\ ratio = \frac{Semi - automatic\ survey\ resources}{Manual\ survey\ resources} \times 100$$

According to the Minister of Home Affairs' Decree No. 690.900-327 of 1996 (Mahmudi, 2007), the classification levels of efficiency are as follows.

Table 1. Efficiency Ratio

Efficiency Ratio (%)	**Criteria**
>100	Not Efficient
90 - 100	Less Efficient
80 - 90	Quite Efficient
60 - 80	Efficient
<60	Highly Efficient

Source: Depdagri, Kepmendagri No.690.900-327 (1996)

Results and Discussion

Road Condition Survey Cost Analysis

The analyzed costs refer to the expenses associated with manual and semi-automated road condition surveys conducted on urban roads in the City of Bandung, covering a total length of 164 kilometers. The cost calculation is based on the 2025 Standard Unit Prices of the City of Bandung, issued by the Mayor of Bandung (Keputusan Wali Kota Bandung Nomor 027/Kep.734-BKAD/2024 Tentang Standar Harga Satuan Dan Standar Biaya Umum Tahun Anggaran 2025, 2024). These calculations are based on the expenses incurred during the manual and semi-automated road condition surveys, including surveyor fees, survey equipment, and data processing tools.

Table 2. Calculation of Manual Road Condition Survey Costs

No.	Cost Component	Unit	Qty	Duration	Unit Price (Rp)	Total Price (Rp)
1.	Personnel Cost					
	Surveyor	person/month	3	3 months	Rp3,500,000	Rp31,500,000
	Data Processing Staff	person/month	1	3 months	Rp4,048,000	Rp12,144,000
2.	Survey Equipment					
	Measuring Tape (50 m)	lump sum	2	1 month	Rp171,600	Rp343,200
	Measuring Wheel	lump sum	2	1 month	Rp499,000	Rp998,000
	Measuring Tape (5 m)	lump sum	2	1 month	Rp36,400	Rp72,800
	Board And Stationery	lump sum	2	1 month	Rp25,000	Rp50,000
	Survey Form	ream	7	1 month	Rp149,600	Rp1,047,200
	Spray Paint	lump sum	35	1 month	Rp30,000	Rp1,050,000
	Smartphone	lump sum	1	1 month	Rp7,798,960	Rp7,798,960
	Rental Car + Driver	unit/month	1	3 months	Rp5,670,000	Rp17,010,000
3.	Processing Equipment					
	Rental Computer for Data Processing	unit/month	1	1 month	Rp500,000	Rp500,000
	Microsoft Office License	unit/month	1	1 month	Rp135,999	Rp135,999
		Total				Rp72,650,159

The calculation cost of Semi-Automatic one as follows:

Table 3. Calculation of Semi-Automatic Road Condition Survey Costs

No.	Cost Component	Unit	Qty	Duration	Unit Price (Rp)	Total Price (Rp)
1.	Personnel Cost					
	Surveyor	person/day	2	5 days	Rp190,000	Rp1,900,000
	Data Processing Staff	person/month	1	1 month	Rp4,048,000	Rp4,048,000
2.	Survey Equipment					
	Smartphone	lumpsum	1	1 month	Rp7,798,960	Rp7,798,960
	Phone Holder	lumpsum	1	1 month	Rp75,000	Rp75,000
	Rental Car + Driver	unit/day	1	5 days	Rp1,000,000	Rp5,000,000

No.	Cost Component	Unit	Qty	Duration	Unit Price (Rp)	Total Price (Rp)
	Carboard (20 * 20 cm); 16 Pcs	roll	3	1 month	Rp3,000	Rp9,000
3.	Processing Equipment					
	Rental Computer For Data Processing	unit/month	1	1 month	Rp500,000	Rp500,000
	Microsoft Office License	unit/month	1	1 month	Rp135,999	Rp135,999
	GPU Cloud Service	unit/day	1	5 days	Rp110,000	Rp550,000
	Google Drive Cloud (2TB)	unit/month	1	1 month	Rp158,000	Rp158,000
Total						Rp20,174,959

Table 4. Calculation of Semi-Automatic Road Condition Survey Costs

Road Survey	Total Cost
Manual	Rp72,650,159
Semi-Automatic	Rp20,174,959

Based on Table 4, the estimated cost required to conduct a manual road condition survey along 164 kilometers of urban roads in the City of Bandung is Rp72,650,159, whereas using the semi-automated method amounts to Rp20,174,959.

Cost Efficiency Analysis

Cost efficiency is calculated based on the amount of cost savings achieved when using the semi-automated method compared to the cost required for the manual survey. The efficiency level attained can be evaluated using the efficiency ratio, which compares the cost of the semi-automated method to that of the manual survey method. The cost savings and efficiency ratio obtained by using the semi-automated method compared to the manual method are as follows.

$$Cost\ Saving\ Efficiency = \frac{cost\ saving}{manual\ survey\ cost} \times 100\%$$

Cost saving efficiency $= \frac{Rp72{,}650{,}159 - Rp20{,}174{,}959}{Rp72{,}650{,}159} \times 100\%$

Cost saving efficiency = 72.23%

Thus, the use of the semi-automated method is 72.23% more efficient compared to the manual survey method.

$$Efficiency\ Ratio = \frac{semi - automatic\ survey\ cost}{manual\ survey\ cost} \times 100\%$$

Efficiency ratio $= \frac{Rp20{,}174{,}959}{Rp72{,}650{,}159} \times 100\%$

Efficiency ratio = 27.77%

Based on the efficiency ratio value, the use of the semi-automated method falls into the highly efficient category in terms of cost, with 72.23% cost-saving efficiency. It shows that the costs required for semi-automatic surveys using machine learning are more efficient than manual surveys.

Road Condition Survey Time Analysis

The analysis of time requirements for road condition surveys is based on the productivity of surveyors for each method. According to a primary survey conducted along 1 kilometer of urban road, specifically on Jalan Terusan Jakarta (Terusan Jakarta Street) in the City of Bandung, the time required for the manual method is 3 hours with a survey team of 3 personnel; whereas the semi-automated method, which involves only the collection of video datasets of road conditions, requires 6 minutes. Another research says that a manual inspection of a one-kilometer segment of a four-lane highway requires a duration of 3 to 4 hours. (Lv et al., 2025). Both durations exclude preparation and personnel mobilization time.

The productivity of manual surveys conducted by a team of three surveyors is calculated as follows.

$$Manual\ Survey\ Productivity = \frac{road\ length}{survey\ time} \times work\ hour$$

Road length	= 1 km
Survey time	= 3 hours
Work hours	= 6 hours/day
Manual survey productivity	= (1 km/3 hours) x 6 hours/day
	= 2 km/day

If calculated for surveying 164 kilometers of road, the time required is as follows:

$$Manual\ survey\ time = \frac{road\ length}{manual\ survey\ productivity}$$

Manual survey time	= 164 km/ (2 km/day) = 82 days
	= 2.733 months ≈ 3 months

The time required to survey 164 kilometers of urban roads in the City of Bandung using the manual method is 82 days, or approximately 3 months.

Meanwhile, the productivity of the semi-automated survey using machine learning, conducted by a team of two surveyors, is calculated as follows.

Road length	= 1 km
Survey time	= 6 minutes = 0.1 hour
Work hours	= 6 hours/day

$$Semi\ automatic\ Survey\ Productivity = \frac{road\ length}{survey\ time} \times work\ hour$$

Semi-automatic survey productivity	= (1 km/0.1 hour) x 6 hours/day
	= 60 km/day

If calculated for surveying 164 kilometers of road, the time required is as follows:

$$Semi\ automatic\ Survey\ Time = \frac{road\ length}{manual\ survey\ productivity}$$

Semi-automatic survey time = 164 km/ (60 km/day)
= 2.733 days ≈ 3 days

The time required to survey 164 kilometers of urban roads in the City of Bandung using the semi-automated method is 3 days. This is much faster than manual surveys that needs 3 months for just data acquisition. This can lead to survey time efficiency.

Time Efficiency Analysis

Time efficiency is calculated by comparing the difference in time required between the two survey methods relative to the longest survey duration. To determine the efficiency category achieved, the ratio of semi-automated survey time to manual survey time is calculated.

$$Time\ Saving\ Efficiency = \frac{time\ saving}{manual\ time\ survey} \times 100\%$$

Time-saving efficiency = $\frac{82-3}{82} \times 100\%$
Time-saving efficiency = 96.34%

Thus, the use of the semi-automated method is 96.34% more time-efficient compared to the manual survey method.

$$Efficiency\ Ratio = \frac{semi-automatic\ time\ survey}{manual\ time\ survey} \times 100\%$$

Efficiency ratio = $\frac{3}{82} \times 100\%$
Efficiency ratio = 3.66%

Based on the efficiency ratio value, the use of the semi-automated method falls into the highly efficient category in terms of time, with time-saving efficiency reaching 96.34%. We found a huge difference in efficiency between the two methods. Using the semi-automatic approach, we collected all the necessary road data in only three days. In comparison, the traditional manual survey took a full three months to complete the same job. Efficiency analysis shows that the time required for semi-automatic surveys using machine learning is much more efficient than manual surveys. So the semi-automatic surveys can be implemented for road condition survey.

Cost Sensitivity Analysis

Sensitivity analysis functions as an analytical technique to evaluate how a model's output responds to variations in its input parameters (Ježek et al., 2018). Its principal application is as an instrument to measure the influence of specific inputs, or groups of them, on the overall uncertainty of the model's results (Saltelli et al., 2019). For the cost analysis of the survey, the cost components considered include surveyor personnel cost, survey equipment, and processing equipment. These components carry different weights in the total cost, depending on the survey method used. The following sensitivity analysis, as shown in Table 5, was conducted by increasing the price of each component by 10% in separate scenarios for each method, to determine which component has the greatest impact on changes in the total cost.

Table 5. Sensitivisty Analysis of Road Condition Survey Cost

Scenarios	Total Cost Manual Survey	Total Cost Semi-Automatic Survey
Base case	Rp72,650,159	Rp20,174,959
+10% Personnel cost	Rp77,014,559	Rp20,769,759
+10% survey equipment	Rp75,487,175	Rp21,463,255
+10% processing equipment	Rp72,713,759	Rp20,309,359

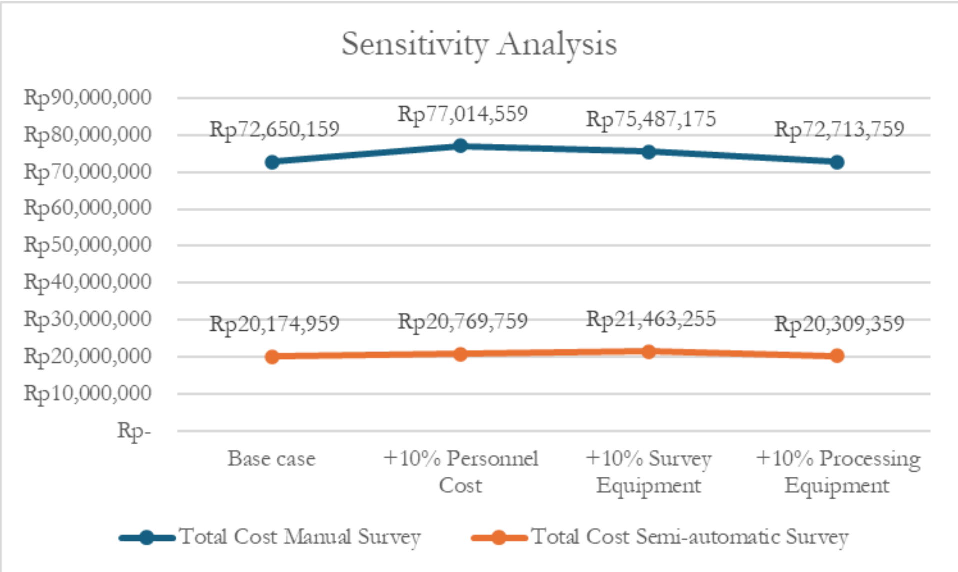

Figure 4. Sensitivity Analysis of Road Condition Survey Cost

Figure 4 reveals that the manual survey method is most affected by changes in personnel costs, indicating high dependence on human resources. It shows that the highest cost occurred when personnel cost increased by +10% and the cost is Rp77,014,559. In contrast, the semi-automatic survey's dominant cost driver is survey equipment. The highest semi-automated survey cost occurred when survey equipment cost increased by +10% which is Rp21,463,255. This condition offers greater long-term cost stability and potential for technological depreciation.

Conclusion

The analysis of cost and time efficiency reveals that the cost savings of 72.23% with an efficiency ratio of 27.77%, while the time savings efficiency is 96.34% with an efficiency ratio of 3.66%. Therefore, the use of the semi-automated method in road condition surveys has proven to be highly efficient compared to the manual survey method. Moreover, based on sensitivity analysis, these findings suggest that semi-automated methods offer a more sustainable approach for road condition monitoring and are better suited for government adoption in large-scale applications.

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